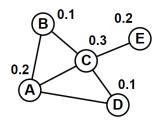
## Final Exam (Graph Neural Networks -Fall 2023)

Full Name: Student ID:

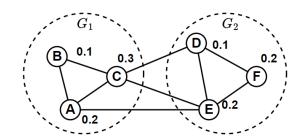
1. Consider an undirected graph G of five nodes A, B, C, D, and E given in the following figure. Each node has initial features that are the numbers standing next to it (i.e., the initial feature of node 'A' is  $h_A^{(0)} = 0.2$ ). According to GraphSAGE model with a AGGREGATE is a MEAN function, the feature of a node i at layer k can be updated as:



$$h_{N(i)}^{(k)} = \text{AGGREGATE}\left(\left\{h_u^{(k-1)}, \forall u \in N(i)\right\}\right)$$
$$h_i^{(k)} = \text{ReLU}\left(h_i^{(k-1)} \parallel h_{N(i)}^{(k)}\right)$$

where || is a concatenation, ReLU(x) = max(0, x), N(i) is the neighbour nodes of node i.

- a) Calculate the feature of each node at k = 1.
- b) Calculate a graph-level embedding  $h_G$  by using a 'Mean' global pooling when k = 1.
- 2. Consider an undirected graph G of six nodes A, B, C, D, E and F given in the following figure. The graph G contains two cluster G<sub>1</sub> and G<sub>2</sub>. Each node has initial features that are the numbers standing next to it. According to ClusterGCN model, the feature of a node *i* at layer *k* can be updated as:



$$\begin{split} h_{N(i)}^{(k)} &= \text{MEAN}\Big(\Big\{h_u^{(k-1)}, \forall u \in N(i), G_u = G_i\Big\}\Big) \\ h_i^{(k)} &= \text{ReLU}\Big(h_i^{(k-1)} \mid\mid h_{N(i)}^{(k)}\Big) \end{split}$$

where  $\parallel$  is a concatenation.

Calculate the output representations of all nodes at layer k = 1.

3. Given a graph with an adjacency matrix A and initial node feature matrix  $H^{(0)}$  as follows:

$$A = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix} \qquad H^{(0)} = \begin{bmatrix} 1 \\ 0 \\ 2 \\ 1 \end{bmatrix}$$

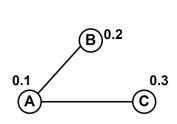
Assume that the output of an GCNII model of all nodes at layer (k) can be calculated as:

$$H^{(k)} = \sigma \left[ \left( \left( 1 - \beta \right) I_n \right) \cdot \left( \left( 1 - \alpha \right) \tilde{A} \cdot H^{(k-1)} + \alpha H^{(0)} \right) \right]$$

where  $H^{(k)}$  denotes the output at layer k,  $\tilde{A}$  is the normalized matrix ( $\tilde{A} = D^{-1}A$ ),  $I_n$  is the identity matrix,  $\alpha = \beta = 0.5$ ,  $\sigma$  is a ReLU function ReLU(x) = max(0,x).

- a) Calculate  $\tilde{A}$ .
- b) Calculate the output representations at layer k = 1.

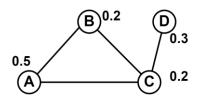
4. Consider an undirected graph G of three nodes A, B, and C given in the following figure. Each node has initial features that are the numbers standing next to it (i.e., the initial feature of node 'A' is  $h_A^{(0)} = 0.1$ ). According to GAT model, the weight matrix W is randomly initialized as [0.5]. The feature of node 'i' at layer (k) can be updated as:



$$h_i^{(k)} = \sigma \left( \sum_{m \in N(i)} \alpha_{im} W h_m \right)$$
  
where:  $\alpha_{im} = \frac{e_{im}}{\sum_{k \in N(i)} e_{ik}}$ , and  $e_{im} = \sigma \left( \text{MEAN}(W h_i, W h_m) \right)$ 

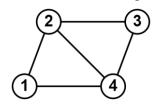
 $\sigma$  is a ReLU function ReLU(x) = max(0,x).

- a) Calculate the attention coefficients  $e_{AB}$  and  $e_{AC}$
- b) Calculate the feature of node 'A' at k = 1.
- 5. Consider an undirected graph G of four nodes A, B, C, and D given in the following figure. Each node has initial features that are the numbers standing next to it (i.e., the initial feature of node 'A' is  $h_A^{(0)} = 0.5$ ). According to GIN model, the parameter is a fixed scalar  $\varepsilon = 0.5$ , the feature of a node i at layer k can be updated as:



$$h_i^{(k)} = (1 + \varepsilon) \cdot h_i^{(k-1)} + \sum_{j \in N(i)} h_j^{(k-1)}$$

- a) Calculate the feature of each node at k = 1.
- b) Calculate a graph-level embedding  $h_G$  by using a 'Max' global pooling when k = 1.
- 6. Consider an undirected graph G of four nodes given in the following figure. The Random Walk Positional Encoding, which is used in SAT model, of a node *i* can be calculated as:



$$p_i^{RWPE} = \left[ \tilde{A}_{ii}, \tilde{A}_{ii}^2, \dots, \tilde{A}_{ii}^k \right]$$

where  $\tilde{A}$  is the normalized adjacency matrix  $\tilde{A} = D^{-1}A$ ,  $\tilde{A}^k$  is the k-step transition probability matrix  $\tilde{A}^k = \underbrace{\tilde{A} \cdot \tilde{A} \cdots \tilde{A}}_{l}$ . Calculate the positional encoding of each node at k = 2.